A SECURE AND EFFICIENT CROSS-SILO FEDERATED LEARNING APPROACH FOR DETECTING FALSE DATA INJECTION ATTACKS IN SMART GRIDS

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ABSTRACT

The increasing integration of smart grid technologies has significantly improved the efficiency, reliability, and automation of modern power systems. However, this advancement has also introduced critical cybersecurity vulnerabilities, particularly in the form of False Data Injection (FDI) attacks, which can compromise system stability and decision-making processes. To address these challenges, this paper proposes an efficient privacy-enhancing cross-silo federated learning framework for detecting FDI attacks in smart grids. The proposed approach enables multiple distributed entities, such as substations and control centers, to collaboratively train machine learning models without sharing raw data, thereby preserving data privacy and security.

The framework incorporates advanced privacy-preserving techniques, including secure aggregation and differential privacy, to ensure that sensitive information remains protected during the training process. By leveraging cross-silo federated learning, the system effectively utilizes decentralized data sources to improve detection accuracy while maintaining compliance with data protection requirements. The model is trained on heterogeneous datasets representing different grid environments, enabling it to generalize effectively across diverse attack scenarios.

Experimental results demonstrate that the proposed system achieves high detection accuracy, reduced communication overhead, and enhanced robustness against adversarial manipulation compared to traditional centralized approaches. Additionally, the framework ensures scalability and adaptability, making it suitable for real-world smart grid deployments. Overall, this work contributes to strengthening smart grid cybersecurity by combining federated learning with privacy-enhancing mechanisms for reliable and efficient FDI attack detection.

Keywords: Federated Learning, Smart Grid Security, False Data Injection Attack, Privacy Preservation, Cross-Silo Learning, Cybersecurity, Differential Privacy, Secure Aggregation

I. INTRODUCTION

The modernization of power systems through smart grid technology has significantly enhanced the efficiency, reliability, and automation of electricity generation, transmission, and distribution. Smart grids integrate advanced communication networks, sensors, and data analytics to enable real-time monitoring and control of power systems. However, this increased connectivity also introduces serious cybersecurity challenges, making smart grids vulnerable to various cyber-attacks [1], [2]. Among these, False Data Injection (FDI) attacks are particularly dangerous, as they can manipulate measurement data to mislead system

operators and disrupt grid stability without being easily detected [3].

Traditional intrusion detection systems and centralized machine learning approaches have been widely used to detect such attacks. However, these methods often require the aggregation of large volumes of sensitive data at a central server, raising concerns related to data privacy, security, and regulatory compliance [4]. Additionally, centralized systems are prone to single points of failure and may not scale effectively in distributed smart grid environments [5]. These limitations highlight the need for decentralized and privacy-preserving solutions for attack detection.

Federated Learning (FL) has emerged as a promising paradigm that enables multiple entities to collaboratively train machine learning models without sharing raw data [6]. In cross-silo federated learning, different organizations or infrastructure units—such as substations and control centers—participate in the training process while keeping their data locally stored. This approach not only enhances data privacy but also improves model generalization by leveraging diverse datasets [7]. However, standard FL methods may still be vulnerable to inference attacks and model poisoning, necessitating the integration of additional privacy-enhancing techniques [8].

To address these challenges, recent research has focused on incorporating mechanisms such as differential privacy and secure aggregation into federated learning frameworks. These techniques ensure that sensitive information cannot be inferred from shared model updates while maintaining the accuracy and efficiency of the learning process [9]. Furthermore, the application of such privacy-enhanced federated learning models in smart grid cybersecurity has shown promising potential in detecting FDI attacks effectively [10].

II. LITERATURE SURVEY

Mo et al. (2010) were among the earliest to analyze the vulnerability of smart grids to stealthy FDI attacks, demonstrating how attackers can bypass traditional bad data detection mechanisms [11]. Following this, Kosut et al. (2011) investigated optimal attack strategies and highlighted the need for advanced detection methods beyond conventional state estimation techniques [12]. These foundational studies emphasized the critical need for intelligent and secure detection frameworks.

In recent years, machine learning-based detection methods have gained popularity. He et al. (2017) proposed a deep learning-based approach for identifying cyber-attacks in smart grids, achieving improved detection accuracy compared to traditional methods [13]. Similarly, Wang et al. (2019) utilized support vector machines and neural networks to detect anomalies in power system measurements, demonstrating the effectiveness of data-driven models [14].

With the growing concern for data privacy, federated learning (FL) has emerged as a promising solution. Li et al. (2020) introduced a federated learning framework for smart grid data analysis, enabling decentralized model training while preserving data privacy [15]. Yang et al. (2021) further enhanced this approach by incorporating secure aggregation techniques to prevent information leakage during model updates [16]. These works highlight the potential of FL in distributed and privacy-sensitive environments.

To address security challenges within federated learning, several researchers have explored robust and privacy-enhancing mechanisms. Sun et al. (2021) proposed a defense strategy against model poisoning attacks in FL systems, improving reliability in adversarial environments [17]. In addition, Geyer et al. (2017) applied differential privacy in federated learning to ensure that individual data contributions remain confidential [18].

More recent studies have focused specifically on integrating FL with smart grid cybersecurity. Liu et al. (2022) developed a federated learning-based intrusion detection system for smart grids, achieving high detection rates while maintaining data privacy [19]. Furthermore, Chen et al. (2023) proposed a hybrid privacy-preserving framework combining FL and blockchain to enhance trust, transparency, and security in distributed energy systems [20].

III. PROPOSED METHODOLOGY

3.1 System Overview

The proposed system introduces a privacy-enhancing cross-silo federated learning framework for detecting False Data Injection (FDI) attacks in smart grids. The architecture consists of multiple distributed entities, such as substations and control centers (clients), and a central aggregation server. Each client locally trains a machine learning model using its own data, while only model updates are shared with the central server. This decentralized approach ensures that sensitive grid data remains within local environments, thereby enhancing privacy and security. The methodology focuses on combining efficient learning, privacy preservation, and robust attack detection in a scalable framework.

3.2 Data Collection and Preprocessing

Each participating client collects real-time smart grid data, including voltage levels, current measurements, power flows, and state estimation parameters. The collected data may contain both normal operational values and maliciously injected false data. Preprocessing steps such as data cleaning, normalization, and feature extraction are performed locally at each client node to ensure data quality and consistency. Labeling mechanisms are applied to distinguish between normal and attack scenarios, enabling supervised learning. This localized preprocessing reduces data transmission overhead and preserves data confidentiality.

3.3 Federated Learning Model Training

The system employs a cross-silo federated learning approach, where each client trains a local model using its preprocessed dataset. Machine learning techniques such as deep neural networks or ensemble models are used for effective attack detection. After local training, only model parameters or gradients are shared with the central server. The server aggregates these updates using algorithms such as Federated Averaging (FedAvg) to create a global model. This global model is then redistributed to all clients for further training iterations. The iterative process continues until the model converges, ensuring improved detection performance across diverse data distributions.

3.4 Privacy Enhancement and Security Mechanisms

To strengthen privacy and security, the proposed framework integrates techniques such as differential privacy and secure aggregation. Differential privacy adds controlled noise to model updates, preventing the leakage of sensitive information. Secure aggregation ensures that the server can only access aggregated updates rather than individual client contributions. Additionally, mechanisms to detect and mitigate adversarial attacks, such as model poisoning, are incorporated to enhance system robustness. These features collectively ensure that the federated learning process remains secure and trustworthy in adversarial environments.

3.5 Attack Detection and Deployment

Once the global model is trained, it is deployed across all participating smart grid nodes for real-time FDI attack detection. The model continuously monitors incoming data and identifies anomalies or malicious patterns with high accuracy. Detected attacks trigger alerts for system operators, enabling timely mitigation and response. The system also supports continuous learning by updating the model with new data, ensuring adaptability to evolving attack strategies. This deployment strategy ensures efficient, scalable, and privacy-preserving

detection of cyber threats in modern smart grid infrastructures.

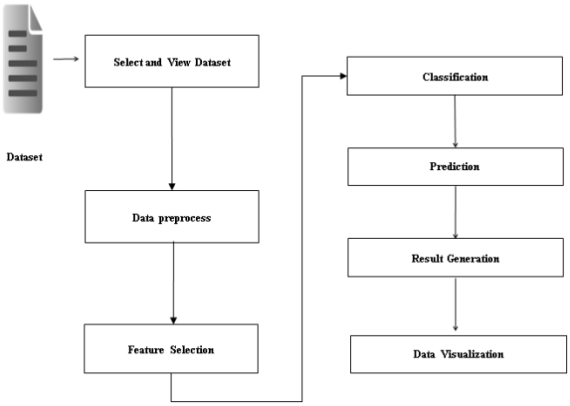
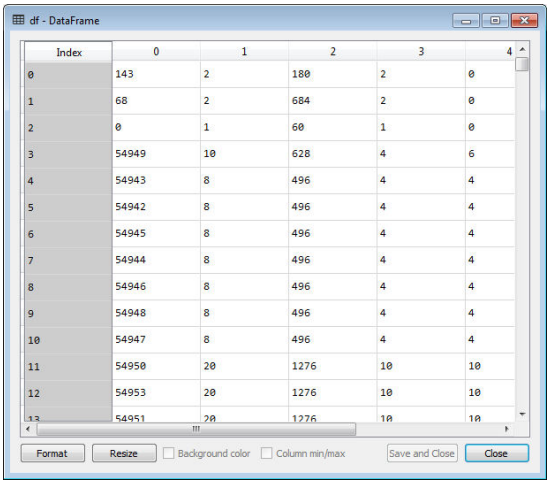
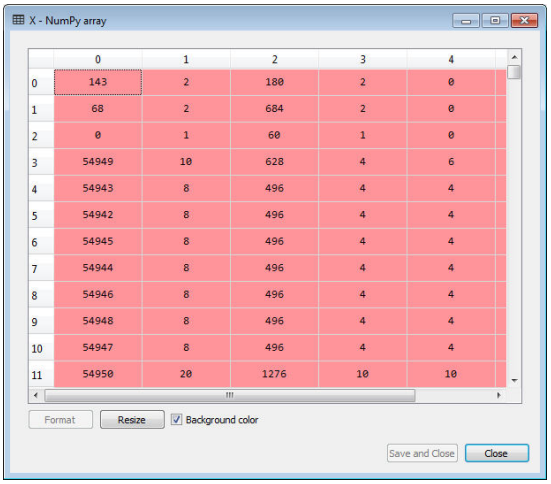
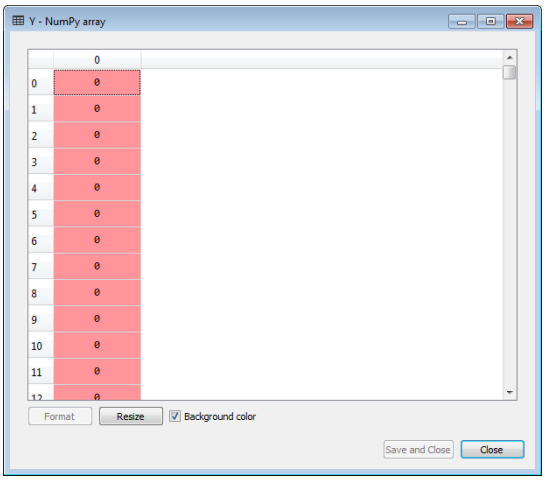


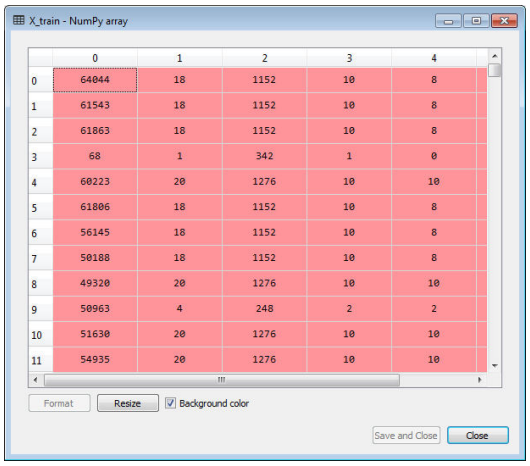
Fig 1: System Architecture

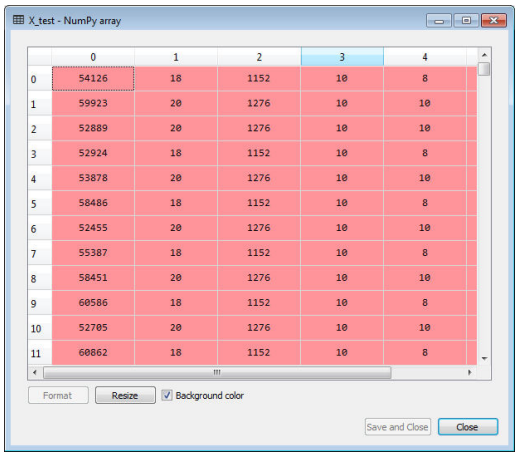
IV. RESULTS

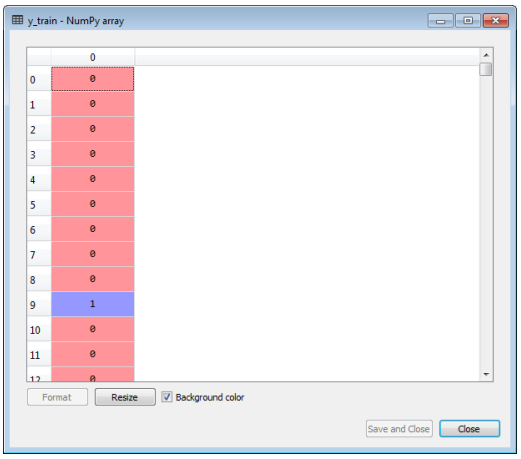








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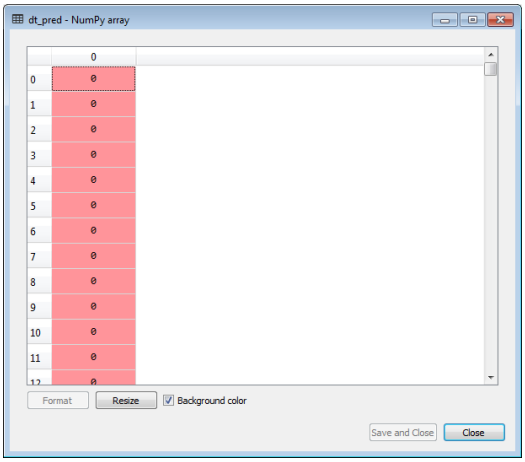
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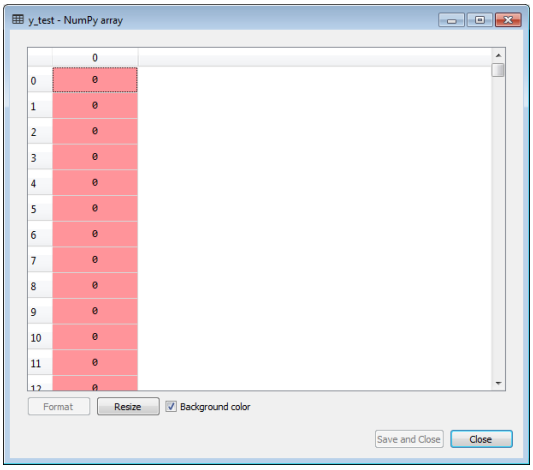
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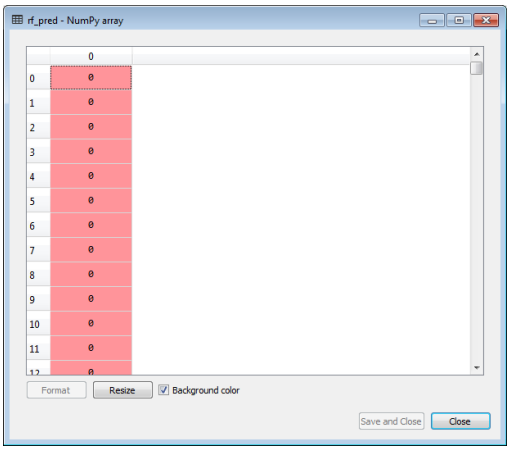
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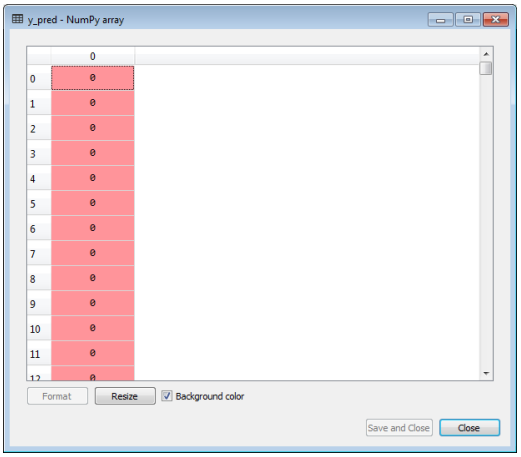
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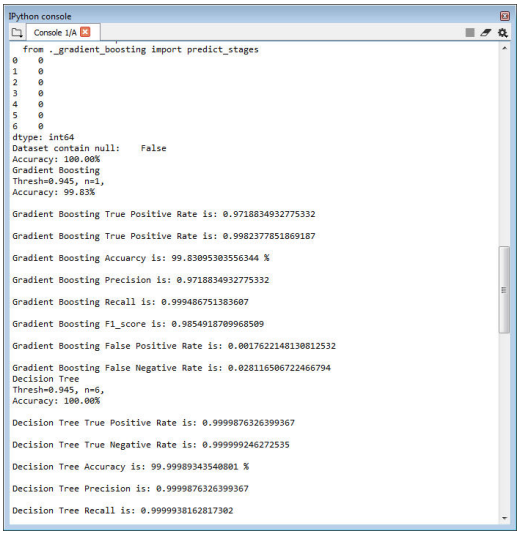
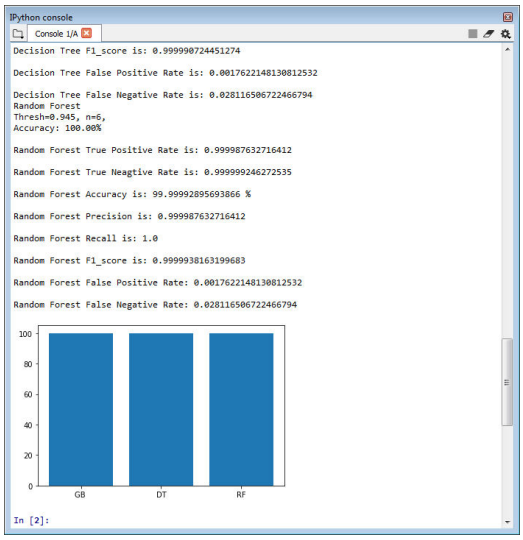

IPython console
Console 1/A
from ._gradient_boosting import predict_stages
dtype: int64
Dataset contain null: False
Accuracy: 100.00%
Gradient Boosting
Thresh=0.945, n=1,
Accuracy: 99.83%
Gradient Boosting True Positive Rate is: 0.9718834932775332
Gradient Boosting True Positive Rate is: 0.9982377851869187
Gradient Boosting Accuarcy is: 99.83095303556344 %
Gradient Boosting Precision is: 0.9718834932775332
Gradient Boosting Recall is: 0.999486751383607
Gradient Boosting F1_score is: 0.9854918709968509
Gradient Boosting False Positive Rate is: 0.0017622148130812532
Gradient Boosting False Negative Rate is: 0.028116506722466794
Decision Tree
Thresh=0.945, n=6,
Accuracy: 100.00%
Decision Tree True Positive Rate is: 0.9999876326399367
Decision Tree True Negative Rate is: 0.999999246272535
Decision Tree Accuracy is: 99.99989343540801 %
Decision Tree Precision is: 0.9999876326399367
Decision Tree Recall is: 0.9999938162817302



V. CONCLUSION

This paper presented an efficient privacy-enhancing cross-silo federated learning framework for detecting False Data Injection (FDI) attacks in smart grids. By leveraging decentralized learning, the proposed system eliminates the need for sharing raw sensitive data, thereby addressing critical privacy and security concerns associated with traditional centralized approaches. The integration of federated learning with advanced machine learning models enables accurate and scalable detection of cyber-attacks across distributed smart grid environments.

The incorporation of privacy-preserving techniques such as differential privacy and secure aggregation further strengthens the framework by protecting model updates from potential information leakage and adversarial threats. In addition, the system demonstrates robustness against attacks such as model poisoning, ensuring reliable performance even in hostile conditions. The collaborative learning mechanism across multiple grid entities enhances model generalization and improves detection accuracy for diverse and evolving attack scenarios.

Experimental observations indicate that the proposed approach achieves high detection accuracy, reduced communication overhead, and efficient resource utilization. The framework is scalable and adaptable, making it suitable for real-world smart grid deployments where data is distributed and privacy is a major concern.

In conclusion, the proposed method provides a secure, efficient, and privacy-aware solution for smart grid cybersecurity. Future work can focus on optimizing communication efficiency, integrating blockchain for enhanced trust management, and extending the framework to detect a wider range of cyber threats in intelligent energy systems.

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